Image Segmentation Techniques for Urban Land Cover Segmentation of VHR Imagery: Recent Developments and Future Prospects

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Since the last decade, remote sensing (RS) sensor technology has seen a steady development, which has refined spatial detail of satellite imagery close to sub-meter resolution of aerial imagery. The development also brought a paradigm shift, from pixel-based to object-based image analysis (OBIA), in remote sensing image processing. OBIA tries to mimic human perception of images as geographic objects. The basic step of geographic object formation in OBIA is image segmentation. Fortunately, image segmentation has been researched in computer vision for the last four decade. However, this doesn't alleviate the segmentation problem because image segmentation is domain specific. This paper reviews image segmentation techniques in the domain of urban land cover segmentation of very high spatial resolution (VHR) satellite imagery. The paper categorizes the segmentation techniques into eight categories namely, clustering, level-set, Markov random field, fuzzy logic, neural network, multi-scale, watershed, and hierarchical split and merges (HSMR). The paper also describes the recently developed techniques, deduces trends, (e.g., widely used techniques and commercially developed techniques) and elaborates on the potential techniques, where a researcher can dig in. The paper concludes that multi-scale and watershed based techniques are the most appropriate for OBIA of VHR images of urban areas.

1. Introduction

Since the launch of the IKONOS satellite in 1999, the spatial detail of satellite images has been improved from several metres to sub-meter resolution. GeoEye-1 (launched in 2008, with 4 spectral bands and 0.41 m resolution of panchromatic (PAN)) and Worldview-2 (launched in 2008 with 8 spectral bands and 0.46m resolution of PAN) leads this group of very high spatial resolution (VHR) (spatial resolution <= 1m) satellite imagery. Due to enhanced spatial resolution, RS images are increasing being used for urban applications, which were dominated by aerial imagery. However, enhanced spatial resolution of satellite images failed to deliver enhanced results. This is because the traditional pixel-based analysis of VHR images failed to utilize an increased spatial variability within the land cover classes of VHR images (Blaschke and Strobl, 2001). This failure led to the surge of object-based image analysis (OBIA) (Carleer et al., 2005, Blaschke et al., 2006 and Blaschke, 2010). OBIA, also known as geographic OBIA (GEOBIA) in RS, follows the logic of the human-based image interpretation of geo-objects (Hay and Castilla, 2006 and Blaschke et al., 2006).

The basic and critical step of OBIA is the generation of image objects using image segmentation (Blaschke, 2010). In general, image segmentation is defined as the process of completely partitioning an image into non-overlapping groups of similar pixels, called as regions, such that adjacent regions are heterogeneous (Pal and Pal, 1993). These regions represent land cover classes such as buildings, trees, and grasslands and are also known as image objects/geo-objects (Blaschke et al., 2006 and Hay and Castilla, 2006). Fortunately, image segmentation has been widely studied in the field of computer vision and other domains (e.g., medical imaging, industry imaging, and range imaging) leading to hundreds of image segmentation techniques (Haralick and Shapiro, 1985, Reed and Buf, 1993, Pal and Pal, 1993, Cheng et al., 2001 and Freixnet et al., 2002). However, the techniques cannot be directly imported to RS because the choice of the image segmentation techniques is domain specific (Pal and Pal, 1993, Zouagui et al., 2004 and Xia and Feng, 2009). For example, in VHR RS domain, a multi-scale analysis is preferable because different ground objects need

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different intrinsic scales whereas in medical image segmentation, the purpose of multi-scale processing is to reduce computational complexity (Pham et al., 2000, Gonzalez and Woods, 2002, Hay et al., 2003 and Benz et al., 2004). In any RS application domain, image segmentation is achieved based on two distinct relationships of a pixel with its neighbouring pixels namely, discontinuity (e.g., edge-based) and similarity (e.g., region-based) (Gonzalez and Woods, 2002). Image segmentation techniques differ based on these two criteria: a) how the discontinuities/similarities (also known as homogeneity/heterogeneity measures) are evaluated; and b) how the pixels are aggregated (e.g., edge contour based and region based) (Gonzalez and Woods, 2002). These criteria are determined based on the goal of segmentation. For example, if the goal of segmentation of figure 1 is to separate water and vegetation areas, spectral properties would suffice. On the other hand, shape and size properties are required to distinguish between a lake and river. Hence, an appropriate image segmentation technique is highly dependent on the domain and goal of OBIA (Shackelford and Davis, 2003, Falkowski et al., 2009, Werff and Meer, 2008 and Zhou and Wang, 2008).

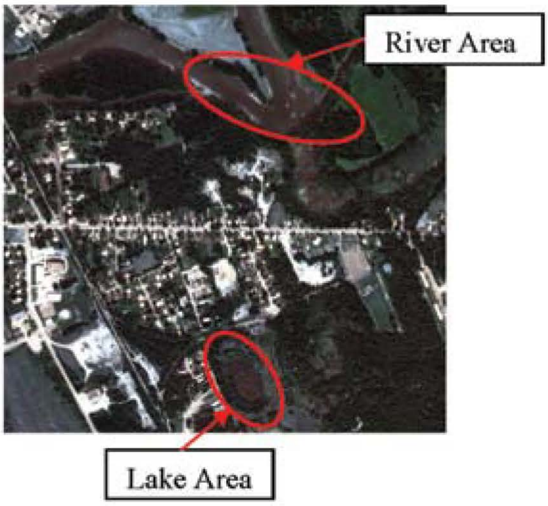

Figure 1: Example of spectral, shape and size information needed for separating vegetation (green) and water (black) as well as river (linear) and lake (closed shape) from an image of Fredericton, Canada. (Source: DigitalGlobe, © Authors purchased the image from DigitalGlobe)

Though image segmentation is often categorized as one of the most critical tasks in image processing, its benefits supersede its drawbacks in the RS domain (Pal and Pal, 1993 and Blaschke et al., 2006). The major benefits of image segmentation based object formation in the RS image analysis are as follows: a) identification of image objects (regions) as perceived by the human eye, especially for VHR imagery; b) utilization of shape, size, and contextual information for analysis; c) utilization of topological relationships for vector based GIS operations; d) reduction in the execution time of classification and increase in its accuracy ; e) minimization of the modifiable areal unit problem (MAUP) caused by dependency of statistical results (e.g., mean and standard deviation) on the spatial units (the chosen spatial resolution of study); and f) minimization the fuzzy boundary problems (Hay et al., 2003, Blaschke et al., 2006 and Blaschke, 2010). However, these benefits are the outcomes of application of an appropriate image segmentation technique of RS domain. Image segmentation has long been studied in domains other than remote sensing (Fu and Mui, 1981, Haralick and Shapiro, 1985, Pal and Pal, 1993 and Cheng et al., 2001). The emergence of OBIA in the last decade led to wide usage of segmentation in remote sensing (Blaschke et al., 2006 and Blaschke, 2010). In RS domain, the major existing review papers are Schiewe (2002), Carleer et al., (2005), Shankar (2007), and Blaschke (2010). The first two review papers are concerned with very few early methods in RS. The third review paper is relatively new and discussed the major categories of image segmentation techniques being used for RS in general. The final paper reviewed about developments of GEOBIA applications, e.g., change detection, disaster and risk management, forest classification and urban feature extraction. The paper also mentioned the wide use of multi-resolution segmentation, implemented in the commercial software eCognition™, for the OBIA applications (Baatz and Schäpe, 2000). In addition, it is also important to identify general rules on how to choose an image segmentation technique for a specific RS application, e.g., urban feature detection and classification. Further, it is also important to identify the widely-used or potential techniques, apart from multi-resolution segmentation, for such applications. This review paper attempts to fill the gaps in these two areas. This paper has identified eight major categories of urban land cover segmentation techniques from earlier reviews (Carleer et al., 2005, Shankar, 2007 and Blaschke, 2010) as: clustering, level-set, Markov random field (MRF), artificial neural network (ANN), fuzzy logic based, multi-scale, watershed, and hierarchical split and merge (HSMR). Further, suitability of each technique for two main RS applications, feature extraction and classification, has been identified. Finally, the paper concludes on the widely-used urban land cover VHR image segmentation techniques and potential categories of segmentation for future researchers of segmentation of urban VHR RS images. The rest of the paper follows a logical progression of factors affecting the choices of segmentation techniques, major categories and a short description of those techniques, and conclusions followed by recommendations.

2. The Factors Governing the Choices of Segmentation Techniques

A human interpreter easily analyses a VHR image into its constituent geo-objects (Lang et al., 2009). This gives both an idea as well as a challenge to develop an automated image segmentation algorithm which segments as efficiently as a human interpreter. A human image interpreter uses visible cues for image analysis, which are synonymous to image interpretation elements (Estes, 1999). Hence, to overcome the challenge, the image interpretation elements are among the most crucial factors in the selection of segmentation techniques. The image interpretation elements (also known as image properties) are as follows: a) spectral, b) spatial, c) texture, d) shape, e) size, f) context, g) shadow, h) connectivity, and i) association. Connectivity, shadow, and association are part of prior knowledge (Estes 1999). In general, prior knowledge is defined as human knowledge about the behaviour and pattern of the ground objects, e.g., the number of classes present in the image scene; the spectral behaviour of classes of objects (NDVI for vegetation), ancillary data (GIS shape layers/maps), and probability distribution (Baltsavias, 2004). All of the segmentation techniques utilize one or more of these interpretation elements. Apart from the aforementioned elements, the analysis at the intrinsic scale (local object scale) is also widely recognized (Hay et al., 2003 and Benz et al., 2004). Hence, these elements along with the scale are key factors in the selection of image segmentation techniques. Among interpretation elements, the spatial property is the preferred element for the image segmentation because it requires aggregation of pixels in the spatial domain (Pal and Pal 1993, Hay et al., 2003 and Blaschke et al., 2006). Moreover, the spatial property is one of the constituents of several other properties, e.g., connectivity represents the spatial relation of distance (e.g., river connectivity); the spatial pattern represents texture; context often represents the spatial context (e.g., a shadow is spatial context of a building); and the scale analysis often studies the spatial patterns (e.g., the study of the ecological spatial pattern using RS image) (Blaschke and Strobl, 2001, Blaschke et al., 2006 and Groom et al., 2006). Apart from utilization of spatial property, the usage complexity of a technique is also a key factor in determining its appropriateness. If software exists for a particular technique, it has less complexity in terms of usage. In addition, for easy to use software, the number of user-defined parameters and their sensitivity towards the final output results should be low. Further, customization ability of software is significant factor for popularity. For example, several popular segmentation software provide the customization capability, e.g., multi-resolution segmentation in eCognition™ provides the ability of using customized features and rule sets (now owned by Trimble Inc.) and ENVI (owned by ITT Visual Information solutions) provides the ability with the interactive data language (IDL) for easy visualization and additional programming (Definiens AG, 2009 and ITT Visual Information Solutions 2011). The next factor is the assessment of the image segmentation results. Marpu et al., (2010) compared several commercially available segmentation techniques based on a quantitative assessment method. They stated that the results of multi-resolution segmentation of Definiens Developer (now eCognition™ Developer 8) are among the best. Although several quantitative assessment techniques exist, the notion of visually pleasing results (especially for VHR images due to enhanced visual details) is still widely popular (Zhang 1997, Zhang et al., 2008, Neubert et al., 2008, Lang et al., 2008, Marpu et al., 2010 and Corcoran et al., 2010). All the factors, stated in the above paragraphs, can be arranged into three different groups: 1) concept based, 2) implementation and use based and 3) evaluation based. While the image interpretation elements and scale are conceptual factors, the usage and parameter complexity belongs to the implementation and use based factor. Similarly, the segmentation quality assessments are part of the evaluation based factor. Top-down and bottom-up approaches (explained in next section) of segmentation, supervised and unsupervised approach, and scale factor of segmentation also add to the conceptual factors (Guindon, 1997, Wuest and Zhang, 2009 and Corcoran et al., 2010). Table 1 summarizes these factors used for the selection of image segmentation techniques. The next section describes several recently developed and commonly used image segmentation techniques in the view of above mentioned factors.

3. Review of Recent Urban Land Cover Segmentation Techniques

With hundreds of image segmentation techniques in place, it is necessary to categorize them for proper representation. The traditional categorization scheme of image segmentation has four categories: a) pixel/point/threshold based, b) edge based, c) region based, and d) hybrid (Spirkovska, 1993 and Schiewe, 2002). Pixel-based techniques employ a global threshold (generally derived from the image histograms) to quantify similarity of features (e.g., pixel values and their standard-deviation) for pixel aggregation whereas, edge based methods find the boundaries and then close the connected boundaries to form regions (Pal and Pal, 1993, Schiewe, 2002 and Blaschke et al., 2006). On the other hand, region based techniques are divided into region growing, merging and splitting, and their hybrids (Blaschke et al., 2006). Region growing starts from seed pixels, a bottom-up approach, and the region is grown until a homogeneity/heterogeneity criterion is satisfied, such as in multi-resolution segmentation technique (Benz et al., 2004). On the other hand, region merging and splitting, a top-down approach, starts by splitting the image into sub-regions and later these regions are merged based on a homogeneity/heterogeneity criterion, such as in hierarchical split and merge technique (HSMR) (Ojala and Pietikäinen, 1999). A hybrid technique is a fusion of two or more of pixel based, edge based, or region based techniques. Despite being widely-used, the traditional categorization scheme has a drawback because the scheme excludes any indication of used image interpretation elements for segmentation. Although the categorization using the major image interpretation elements is possible, the categorization lacks a description of the models to be used for segmentation. Here, a segmentation model is a set of assumptions and processes/steps to perform segmentation. For example, the texture based categorization by Reed and Buf (1993) utilizes several models (such as MRF, Fuzzy, and ANN) but has no clear indication of the best model for a specific application. Hence, to be more specific about implementation of techniques, a model/approach based categorization scheme is selected (Shankar 2007). The models/approaches provide explicit information regarding steps of the techniques, used interpretation elements, and possible modifications in their implementation. The models/approaches selected for this review are as follows: a) Clustering approach, b) Level-set, c) MRF model, d) ANN model, e) Fuzzy model, f) Multi-scale model, g) Watershed model, and h) HSMR model. The models listed above can be further categorized as: i) mathematical models namely, probability and statistics based optimization model (Level-set, MRF, and ANN model), and fuzzy logic based model; and ii) conceptual models (e.g., Multi-scale, Watershed, and HSMR model). It is important to note that the above mentioned models/approaches are by no means complete in categorizing all the RS segmentation techniques but they do represent most of the segmentation techniques used for VHR urban area images (Carleer et al., 2005 and Shankar et al., 2007). A few other models/approaches namely, object-background model and edge-based approach are obsolete and are not discussed here. Interested readers can go to Pal and Pal (1993) for the details of these models/approaches. The next few sub-sections describe the recently developed urban land cover segmentation techniques, their interpretation elements, their parameters and implementation complexity, and VHR images for testing the segmentation results, if any.

Table 1: The rules/factors governing the choices of selection of segmentation techniques for remote sensing

Conceptual Factors	Implementation and ease of use	Evaluation factor
Top-down and bottom-up approach	User-defined parameters and implementation complexity, e.g., existing software and its ease in usage and customization	Quantitative evaluation, e.g., Zhang (1997), Corcoran *et al.* (2010)
Supervised and Unsupervised approach		Visual accuracy
Multi-scale or hierarchical		
Interpretation elements, e.g., Spectral, spatial, contextual, shape, size and prior knowledge		

3.1 Clustering Approach

Clustering is based on the concept of pixel grouping but it is conceptually different from segmentation. While traditional clustering techniques (K-means and ISODATA) rely on aggregation in spectral measurement space, segmentation relies on aggregation in the spatial domain (Haralick and Shapiro, 1985). However, image segmentation is possible using clustering (Pal and Pal, 1993). Moreover, the spatial domain can also be included in clustering (Haralick and Shapiro, 1985). Even with the spatial domain, most of the clustering techniques need an initial number of clusters (segments), which is difficult to estimate for unsupervised segmentation (Pal and Pal, 1993). Hence, a successful clustering-based segmentation technique for a VHR image needs inclusion of the spatial domain and automatic determination of the initial number of cluster/segments. The next paragraph deals with an example of a recently developed clustering technique satisfying these two requirements. Wang et al., (2010) proposed a region based image segmentation (RISA), which is a hybrid of K-means clustering and region merging approaches and utilises spectral, spatial, shape, and size properties. RISA has five crucial steps: a) K-means clustering for seeds selection, b) segment initialization for every pixel in the image, c) automatic seed generation based on the clustered image, d) region growing from the generated seeds, and e) merging the over-segmented regions. Though the technique is conceptually sound, it suffers from parameter complexity because it requires more than five user-defined parameters to estimate. However, the process has been successfully implemented in software and has been applied to an urban Quickbird image. The obtained results are reportedly comparable to that of multi-resolution segmentation technique of eCognition™ (a very popular technique, as mentioned by Blaschke (2010)). Further, the technique offers multi-scale analysis, which is crucial for VHR segmentation (Hay et al., 2003, Benz et al., 2004 and Blaschke et al., 2006). A few other significant techniques include fuzzy clustering based approaches (e.g., Fan et al., 2009), to be described in the fuzzy model section. Though clustering techniques have been used for the last four decades, the techniques have relatively few applications in urban land cover segmentation using a VHR image.

3.2 Mathematical Models Based Image Segmentation

3.2.1 Level-set model

Level-set model, also formulated as active contour model or snake model, tracks boundaries of the object by minimizing the defined energy function with appropriate boundary conditions (Peng et al., 2005 and Karantzalos and Argialas, 2009). Level-set model has been recently used in urban remote sensing for segmentation applications, e.g., urban features extraction (buildings and roads) by Karantzalos and Argialas (2009) and urban change detection by Bazi and Melgani (2010). Level-set model has several promising features which are as follows: a) it generates vector contours; b) it successfully extracts urban features using spectral and spatial features from aerial and satellite imagery, e.g., building detection and road extraction (Peng et al., 2005 and Mayunga et al., 2007); and c) it has very few parameters (Karantzalos and Argialas, 2009). However, compared to other models relatively few relevant level-set based research papers can be found for urban VHR land cover segmentation. Further, most of the papers have segmentation based feature extraction applications. Hence, more experimentation is required for deducing the suitability of level-set models in urban land cover segmentation, especially in the case of classification.

3.2.2 MRF model

While clustering performs optimization in the measurement space, MRF is based on statistical and probabilistic theory based optimization. As with any optimization problem, MRF model has three basic steps: a) problem representation, b) formulation of the objective function, and c) optimization of the objective function (Li 2009). The image segmentation problem is represented as a discrete labelling problem in MRF model. The objective function is generally formulated using a probabilistic estimation, e.g., maximizing a posterior (MAP) estimation and maximizing posterior marginal (MPM) (Li 2009). The optimization problem has two steps: a) parameter estimation and b) MAP/MPM estimation or the equivalent (Li, 2009). In practical applications, MRF optimizations are computationally very expensive and are obtained using the equivalence of MRF with Gibbs random field (GRF) (Geman and Geman, 1984 and Li, 2009).

MRF models based on GRF employ the spatial context using interactions of different potentials (as shown in figure 2 and mathematically known as Markovian property) and prior knowledge of the probability functions (generally a known probabilistic distribution). Subsequently, MRF is an attractive technique for texture based segmentation (Bouman and Shapiro, 1994 and Poggi et al., 2005). Further, MRF can be modified to perform a multi-scale segmentation, as proposed by Bouman and Shapiro (1994), where the pixels across different resolutions (derived from the resolution of the original image) are considered to be in Markovian chain or following Markovian property. Although MRF uses spatial context, its implementation is complex and requires prior knowledge of an initial number of segment labels (D'Elia et al., 2003 and Poggi et al., 2005). One of the recent applications of MRF in an urban VHR image is by Liu et al., (2009). Liu et al., (2009) used wavelet-based multi-resolution representation of tree-structured MRF (WTS-MRF) (proposed by D'Elia et al., 2003) for supervised image segmentation and classification of a semi-urban Quickbird image. The reported kappa classification accuracy was around 80% with only one user-defined parameter.

P(1,1)	P(1,2)	P(1,3)	P(1,4)	P(1,5)
P(2,1)	P(2,2)	P(2,3)	P(2,4)	P(2,5)
P(3,1)	P(3,2)	P(3,3)	P(3,4)	P(3,5)
P(4,1)	P(4,2)	P(4,3)	P(4,4)	P(4,5)
P(5,1)	P(5,2)	P(5,3)	P(5,4)	P(5,5)

Figure 2: P(3,3) represents pixel and its 8 point neighbourhood (gray)

Although popular in the non-RS domain, MRF has found little usage in the urban land cover segmentation of VHR images (including both urban and non-urban) (Pal and Pal, 1993 and Shankar, 2007). Several non-VHR image based image segmentation techniques include Bouman and Shapiro (1994), Sarkar et al., (2002), D'Elia et al., (2003), Poggi et al., (2005), and Yang et al., (2008). The lack of the applications of MRF based techniques to urban image segmentation may be attributed to MRF's implementation complexity as well as lack of commercial software based on it (Kato (1994), D'Elia et al., (2003)). Further, urban classes are too complex to be modelled by statistical distributions, as required in MRF based segmentation (Herold et al., 2003 and Platt and Rapoza, 2008). To summarize, it can be said that MRF has not been widely used for urban land cover segmentation of VHR imagery.

3.2.3 ANN model

While MRF is a probabilistic optimization, ANN is a machine learning based optimization technique. ANN simulates the functioning of the human brain processing elements, i.e., neurons (Tso and Mather, 2004). Neurons of ANN are cobwebbed to form a learning network which requires training data and produces a generalized framework for segmentation/classification of the rest of the data, as shown in Figure 3(a) and (b). ANN has been widely used for pattern recognition applications (Tso and Mather, 2004). The basic ANN model is a multi-layer Perception (MLP) with the training process as a back-propagation algorithm, which follows supervised methodology (Atkinson and Tatnall, 1997). However, unsupervised training based networks are also possible, e.g., Kohonen's self-organizing maps (SOM), adaptive resonance theory 1 (ART1) (for binary values), ART2 (for continuous values), and fuzzy ART. A conceptual and detailed description of ANN with respect to remote sensing can be found in several research papers such as Tso and Mather (2004), Mather (2004), Atkinson and Tatnall (1997), and Mas and Flores (2008). Each of them analysed the advantages and disadvantages of using ANN in RS. The advantages of ANN, as specified by these research papers, are because ANN:

a) Performs when the dataset is fairly complex and no single statistical distribution can model the dataset properly.
b) Incorporates a priori knowledge and realistic physical constraints into analysis.
c) Uses multisource data (of both remote sensing and non-remote sensing).
d) Generalizes noisy patterns, e.g., in case of missing and imprecise data.

However, ANN has a long list of disadvantages too (Mather 2004). The disadvantages, as specified by Mather (2004) and Mas and Flores (2008), are:

a) Problems in designing the neural network: There are no specific guidelines for a user to decide on the parameters of the network, e.g., the number of hidden layers, the number of neurons on each hidden layer, the number of iterations, the learning rate, etc.

b) Problems in training, e.g., training time may be too long depending on the network design, experience is required for the selection of appropriate training data for generalization; over-training or under-training may result from the network design.
c) Problems in network's convergence to a solution, e.g., the network might converge on a local minimum value instead of a global minimum value, which is desirable.

Traditionally, ANN has been mainly used for urban land cover classification with few applications for urban land cover segmentation (Wang and Terman, 1996). Recently, several ANN segmentation techniques in the RS domain have been proposed such as: 1) Chen et al., (1997) utilized spatial information in a fuzzy ART2 approach for the segmentation of a SPOT image; 2) Gang (2005) used probabilistic neural network for the segmentation of a Landsat ETM+ image; 3) Ouma and Tateishi (2007) used spectral and spatial information for multi-resolution image segmentation of a Landsat ETM+ image by a multi-spectral anisotropic diffusion based neural network technique; 4) Awad et al., (2007) used a hybrid of Kohonen SOM and genetic algorithm for the segmentation of Landsat, SPOT, and IKONOS images; and 5) Li et al., (2007) used pulse coupled neural network (PCNN) for segmentation of an IKONOS image. Apart from Li et al., (2007), none of the above-mentioned segmentation techniques has been applied for the specific purpose of the urban land cover segmentation of a VHR image. Li et al., (2007) improved PCNN, proposed by Kuntimad and Ranganath (1999), by including spatial information in a multi-scale segmentation process. However, the technique was applied to the red band image of a multi-spectral IKONOS image. Further, the technique suffers from the parameter complexity because it requires a minimum of five user-defined parameters. These factors suggest that the improved PCNN technique is not attractive for VHR segmentation. Similar to MRF model, ANN also has few applications related to urban land cover segmentation. This conclusion is further supported by the fact that out of the numerous applications of ANN, e.g., classification, change detection, georeferencing, cloud classification, fusion, ecology, and soil moisture, (specified in the review of RS techniques using ANN by Mas and Flores (2008)), very few urban land cover segmentation applications were found. However, ANN has a strong application in the case of VHR image classification (Mas and Flores, 2008). Further, it can incorporate a priori knowledge and realistic physical constraints, which may be useful for supervised image segmentation (Schiewe, 2002 and Mather, 2004).

3.2.4 Fuzzy model

ANN and MRF are based on the traditional mathematics of bivalent logic whereas fuzzy model relies on multivalent logic, as proposed by Zadeh (1965). While bivalent logic is based on true and false scenarios, fuzzy logic quantifies linguistic variables with multiple scenarios, e.g., rich and poor, young and old, high and low, large and small, etc. (Zadeh, 1975). Similar to ANN, fuzzy logic can also include prior knowledge and realistic physical constraints (Tso and Mather, 2004 and Platt and Rapoza, 2008).

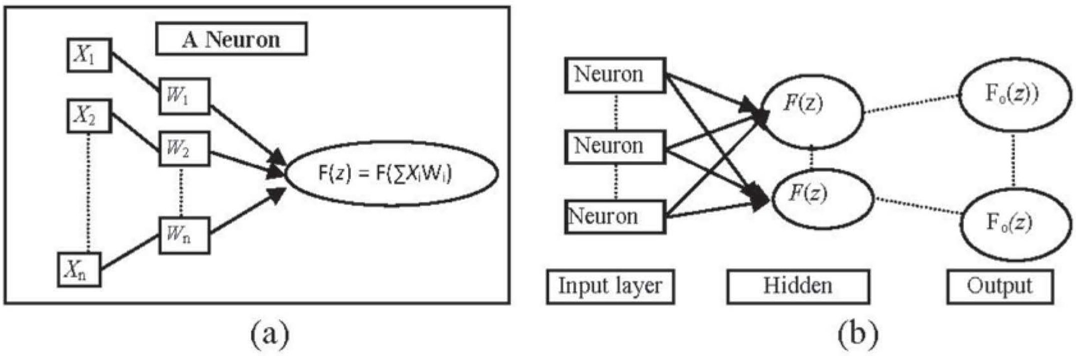

Figure 3: (*a*) shows the structure of a simple neuron with inputs as X_is, which are linearly combined with the weights W_is to form *z*, and then *z* is passed on to a threshold function to get the output. (*b*) shows the formation of a simple neural network by the combination of several neurons with hidden layers represented as dots with different threshold functions, F & F_o at different layers

In a VHR image, ambiguity/fuzziness across segment boundaries is unavoidable (Benz et al., 2004). This makes fuzzy logic a better candidate when compared to MRF and ANN models. Further, fuzzy logic has been recently used in urban VHR based applications, such as classification, feature extraction, and change detection (Benz et al., 2004, Hester et al., 2010, Mohammadzadeh and Zoej, 2010 and Aldred and Wang, 2011). A conceptual and detailed description of general methodology of fuzzy logic, applicable to image segmentation, can be found in Tso and Mather (2004) and Tizhoosh and Haussecker (2000). Further, Tizhoosh and Haussecker (2000) categorized fuzzy image segmentation into five major categories as:

a) Fuzzy Image clustering approach: it refers to clustering algorithm with fuzzy inputs, which generate fuzzy clusters, e.g., fuzzy c-means (FCM) (Canon et al., 1986 and Fan et al., 2009).
b) Fuzzy rule based approach: it utilizes image features in the linguistic variables based fuzzy rules, e.g., IF pixel is DARK and the spatial neighbourhood is homogeneous, then pixel belongs to BACKGROUND.
c) Fuzzy measures based approach: it utilizes fuzzy measures (e.g., fuzzy correlation and fuzzy entropy measures) to evaluate fuzzy thresholds to be used for fuzzy segmentation (Pal et al., 2000).
d) Fuzzy geometry based approach: it utilizes fuzzy geometrical properties (e.g., fuzzy compactness, fuzzy length, and fuzzy area) to evaluate fuzzy thresholds to be used for fuzzy segmentation (Pal et al., 2000).
e) Fuzzy integrals based approach: fuzzy integrals aim to aggregate information from different outputs, such as segmentation and classification algorithms. Fuzzy integrals are essentially non-linear functions, which are defined on the basis of fuzzy measures. Di et al., (2008) and Tian et al., (2009) are two examples of research articles, which utilized fuzzy integrals for change detection.

Out of the five categories, the most researched category in RS image segmentation is FCM. Similar to clustering, the basic FCM requires an initial number of clusters and lacks utilization of the spatial domain (Fan et al., 2009). Fan et al., (2009) proposed a single point iterative weighted FCM (SWFCM) which tackles the problem of the initial number of clusters by collecting prior information regarding image classes and uses the prior information to calculate the weights/effectiveness of data attributes (e.g., mean and standard deviation) for enhancing the outputs of clustering based segmentation. Moreover, the technique uses a single point adjustment method to effectively identify the initial centres of clustering and spatial behaviour of the selected data attributes. However, the technique requires initialization of four user-defined parameters but the parameters are relatively easy to estimate, as specified by the research paper of the technique. Although Fan *et al.* (2009) applied the technique on a Landsat TM image; the technique has potential for urban VHR image segmentation because of utilization of the spatial information and lesser parameter complexity. Hasanzadeh and Kasaei (2010) also proposed a FCM based technique which included the spatial information. They modified membership-connectedness (MC) based technique, which utilizes the ideas of fuzzy connectedness in a FCM technique along with the spatial relations among pixels, by using size-weighted Fuzzy clustering. Further, they claimed that MC suffers from the spatial redundancy problem, which they reduced by a watershed transform based image tessellation method. However, the technique requires the approximate number of segments to be generated. Therefore, the prior knowledge of the number of segments of the data set should be available. Similar to the last explained technique; this technique was applied on Landsat-7 image. However, the technique utilized the concept of fuzzy boundaries and spatial information, which is appealing for urban VHR segmentation (Benz et al., 2004).

The final technique to be discussed here is fuzzy image regions method (FIRME) proposed by Lizarzo and Barros (2010). In the first step, they performed fuzzy classification using a supervised regression technique, such as generalized additive models (GAM), for generating fuzzy-fuzzy image regions using original pixels. Then, the fuzzy-fuzzy image regions were segmented to generate crisp-fuzzy (CF) regions (crisp boundaries and fuzzy core) and fuzzy-crisp (FC) regions (fuzzy boundaries and certain cores). The features, such as area, geometry, texture, mean, etc., of FC and CF regions were optimized to generate the best discriminating features for each class. The optimized features were used for subsequent de-fuzzification and classification using the support vector machines algorithm. The technique is attractive because it can include prior knowledge (in selecting features for optimization) and also utilizes spectral and spatial context properties with fewer parameters. Moreover, the specified technique was experimented on a Quickbird image of mixed-urban area and generated up to 85% classification accuracy. The recently developed fuzzy segmentation techniques, discussed in this section, include the spatial domain but they still lack multi-scale analysis. Further, these techniques require prior knowledge of the data or classes. Hence, supervised segmentation and segmentation based feature extraction are the best suited applications. It can be concluded that fuzzy segmentation misses the list of popular techniques for general urban VHR image segmentation (especially unsupervised segmentation), but the fuzzy segmentation approach has high customization possibilities suitable for a supervised segmentation (Mohammadzadeh and Zoej, 2010 and Aldred and Wang, 2011).

3.3 Conceptual Models Based Image Segmentation

The conceptual models (multi-scale model, watershed, and HSMR model) are based on the concepts by which the image objects can be represented and analysed for effective segmentation.

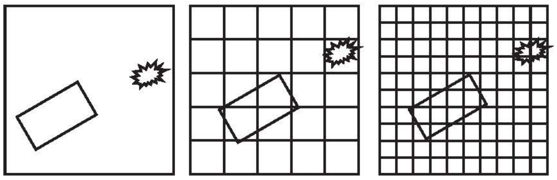

Figure 4: shows the concept of the appropriate scale of representation of an object. Two objects of rectangular, R, and star, S, shaped have been taken as examples, where *a*), at 20m spatial resolution (SR), shows that both the objects are undetectable; *b*), at 5m SR, shows that R is detectable but S is not; and *c*), at 1.25m SR, shows that both are detectable. Image Source: Blaschke 2010. Courtesy: ISPRS

For example, figure 4 shows that the concept of multi-scale analysis for effective identification of both the objects. In conceptual models, the approach of segmentation determines how the object is viewed for representation, e.g., a bottom-up approach forms image objects starting from a seed-pixel and a top-down approach starts by splitting the image into homogeneous objects (Guindon, 1997). While multi-scale model can be implemented using both top-down and bottom-up approaches, HSMR uses a top-down approach and watershed uses a bottom-up approach (Hay et al., 2003, Beucher, 1992, Wuest and Zhang, 2009). The superiority of top-down or bottom-up approach is still a matter of debate and any should be fine for effective segmentation (Castilla et al., 2008). The next few subsections describe the recently developed and widely used techniques of the above mentioned three conceptual models namely multi-scale, watershed, and HSMR.

3.3.1 Multi-scale model

It has been long established that scale is important in the analysis of RS imagery (Woodcock and Strahler, 1987). Further, a single scale is often considered inappropriate for the analysis, which should be carried out at different hierarchical scales, especially for urban VHR images (Benz et al., 2004, Ju et al., 2005 and Platt and Rapoza, 2008). The scale of an object can be defined as the level of aggregation and abstraction at which an object can be best described (Benz et al., 2004). For example, an object which is smaller than the spatial resolution of the image cannot be identified because the scale of observation is limited by the resolution, as shown in figure 4. Though scale and resolution are closely related, they are not the same (Benz et al., 2004). Further, the concept of a meaningful object (i.e., an image object which represents a ground object, e.g., buildings, roads, etc.) varies based on the applications and the image interpreter (Hay and Castilla, 2006, Tian and Chen, 2007). For example, in feature extraction, each building is a meaningful object and improper segmentation of a road object is not a problem whereas, in segmentation based classification, both the roads and buildings constitute meaningful objects (Benz et al., 2004 and McGuinness and O'Connor 2010). Hence, it is essential to analyse RS imagery at multiple scales such that different meaningful objects can be extracted at their best scales (Hay et al., 2003, Benz et al., 2004 and Hay and Castilla 2006).

Scales are represented hierarchically in mainly two ways: 1) based on the scale space theory and 2) based on segmentation levels. Scale space theory refers to connected images of different coarse resolutions obtained from the image with the finest resolution (Lindberg 1996 and Hay et al., 2003). For example, figure 4(a) and (b) can be obtained from figure 4(c) by simple averaging or other scale representation techniques, such as wavelet, pyramid graph model, and quadtree (Bouman and Shapiro, 1994 and Liu et al., 2009). On the other hand, segmentation levels are represented as different segmentation outputs, where each lower segmentation output/level is connected to the next higher level in such a way that merging of object boundaries at the lower level forms the next higher level, e.g., multi-resolution segmentation (Benz et al., 2004 and Wang et al., 2010). The latter approach is more popular and its most widely-used technique is multi-resolution segmentation (Blaschke, 2010). Multi-resolution segmentation is based on multi-fractal analysis also known as fractal net evaluation approach (FNEA) (Baatz and Schäpe, 2000, Blaschke et al., 2006 and Blaschke, 2010). Multi-resolution segmentation utilizes a heterogeneity parameter which is defined based on spectral heterogeneity (i.e. standard deviation), and shape heterogeneity (based on an object's compactness and smoothness) for a hierarchical region merging procedure (Benz et al., 2004). Further, multi-resolution segmentation (FNEA) has been implemented in commercial software known as eCognition™ Developer (now owned by the company Trimble Inc.) available since 2000 (Blaschke, 2010). Moreover, Neubert et al., (2008) and Marpu et al., (2010) concluded after quantitative evaluations of several segmentation based software that FNEA of eCognition™ is one of the best segmentation techniques for urban land cover segmentation as well as other RS applications.

Though widely popular, FNEA requires an appropriate estimation of three user-defined parameters (scale value, shape weight, and compactness weight) for appropriate segmentation, which is a critical issue (Hay et al., 2003 and Tian and Chen, 2007). Several researchers have tried to optimize the parameters, e.g., Maxwell and Zhang (2005), Tian and Chen (2007), Costa et al., (2008), Drăgut et al., (2010), but their wide applicability is still to be established. Apart from FNEA, hierarchical image segmentation (HSEG), originally proposed by Tilton (1998) and later modified as recursive HSEG (RHSEG) by Tilton (2003), is another multi-scale based technique. RHSEG essentially uses a hybrid of region growing and spectral clustering techniques to perform multi-scale segmentation. The segmentation is represented by hierarchical levels, as defined in the first paragraph of this section. Although RHSEG is implemented as software, it lacks popularity for urban VHR image segmentation due to the lack of generation of visually pleasant results as well as due to low segmentation accuracy (Neubert et al., 2008). Hay et al., (2003) and Hay and Marceau (2004) described two more multi-scale based techniques, namely Linear scale-space and blob-feature detection (SS), and multi-scale object-specific analysis (MOSA). Both MOSA and SS are based on scale space theory (Lindberg, 1994). Apart from scale space, MOSA also uses marker-controlled watershed segmentation for effective segmentation outputs (Meyer and Beucher, 1990). Hay et al., (2003) supported these two techniques over the popular FNEA. However, they also reported that SS has high computational complexity. As per Hay et al., (2003), both MOSA and SS have no parameters complexity and are conceptually sound. However, MOSA and SS lack popularity because of the absence of implementation in commercial software as well as the lack of comprehensive testing on a wide variety of VHR images. In addition, a few other recent multi-scale techniques applied to urban land cover segmentation of VHR images include: 1) multi-scale morphological segmentation by Pesaresi and Bendiktsson (2001), 2) TS-MRF by Liu et al., (2009), 3) multi-scale watershed by Zhaocong et al., (2009) (discussed in the next section on watershed), and 4) RISA (based on clustering) by Wang et al., (2010). Most of these techniques require comprehensive testing for evaluating the effectiveness for urban land cover segmentation. To summarize, multi-scale model is the most widely used and recognized technique for urban land cover segmentation with multi-resolution segmentation being the most popular (Blaschke, 2010). Further, most of the researchers ascertained that multi-scale segmentation is the most effective way of urban land cover segmentation of VHR image (Hay et al., 2003, Blaschke et al., 2006, Platt and Repoza, 2008 and Blaschke, 2010).

3.3.2 Watershed model

Watershed segmentation is another conceptual model for image segmentation. Watershed model represents an image as a topographic surface. The model assumes that if water effuses out from selected minimum points across the image, then the boundaries where the flooded regions from each minimum point meet constitute the desired segmentation regions (Beucher, 1992 and Kim and Kim, 2003). Due to this representation, watershed segmentation is also known as a morphological segmentation technique (Beucher, 1992 and Pesaresi and Benediktsson, 2001). One of the most effective implementations of watershed segmentation is marker controlled (MC) watershed segmentation, proposed by Meyer and Beucher (1990). Watershed techniques are relatively new compared to the previously discussed models. The general steps for the most common MC watershed segmentation of a single band image are: a) pre-processing the image with a median or a similar filter to eliminate noise, e.g., Gaussian filter, anisotropic diffusion filter, or Peer Group filter (PGF) (Chen et al., 2006 and Ons and Tebourbi, 2009); b) transforming the image into a gradient image using gradient operators; c) finding object markers using a region's local minima; and d) effusing water from each marker point until the boundaries across the markers meet. The resultant boundaries are watershed contours or segment boundaries (Beucher, 1992, Carleer et al., 2005). The major challenges of this approach are: a) suitable selection of number and location of markers; b) over-segmentation, a common outcome of traditional watershed segmentation (Chen et al., 2006, Li and Xiao, 2007, Castilla et al., 2008); and c) efficient computation of the gradient image, especially for multi-band images. The next few paragraphs describe a few examples of recently developed watershed segmentation techniques combating the above mentioned challenges for urban VHR image segmentation.

The first technique to be discussed is a multi-scale watershed segmentation technique by Chen et al., (2006). They used PGF, a non-linear filter, for noise removal and image smoothing. The smoothened image was segmented using a floating point-based rain-falling algorithm, as proposed by Smet and Pires (2000). The segmentation required initial over-segmentation of the proposed watershed based technique. The over-segmented image was subjected to a hierarchical multi-scale region merging algorithm based on the spectral, shape, and compactness heterogeneity, similar to eCognition™ software's multi-resolution approach. The technique is lucrative since it uses spectral, spatial, shape, and size features along with multi-scale analysis. However, the technique was applied to an IKONOS PAN image (single channel) only. The technique also requires four parameters where the three parameters are the same as the three parameters of eCognition™'s multi-resolution approach. The high number of the parameters is a disadvantage of this technique. Countering the single channel problem, a multi-channel and multi-scale watershed segmentation technique was proposed by Li and Xiao (2007). They applied a multi-scale vector-based gradient algorithm using multi-dimensional dilation and erosion for gradient image generation from a multi-spectral Quickbird image. Further, they applied an irrelevant-minima suppression algorithm, proposed by Wang (1997), for efficient minimum point generation to suppress over-segmentation. The technique has potential for effective urban VHR image segmentation. However, more experiments are required on different VHR images to test the reliability of the technique for urban VHR image segmentation. As specified in the earlier paragraphs, the effective gradient image generation for watershed segmentation (especially for textured images) is essential. Hence, several techniques for the effective gradient image generation of textured images have been proposed. These techniques can be followed by a multi-scale analysis of a watershed algorithm. For example, Ons and Tebourbi (2009) calculated several texture features using Gabor filters for the gradient image generation; QiuXiao et al., (2004) used H-index based texture features for the gradient image generation; and Zhaocong et al., (2009) used texture features in the region merging step of a granular computing based multi-scale analysis of watershed segmentation. MOSA, a multi-scale and modified MC based watershed segmentation, was proposed by Hay and Marceau (2004). They used an object-specific up-scaling (OSU) algorithm, an algorithm to generate images of different resolutions starting from the finest resolution, for the multi-scale analysis. The up-scaled images and their mean images were used to calculate the gradient image. Further, the up-scaled images were used for the proposed technique, which is a modified MC watershed segmentation technique. The technique was applied to a non-urban IKONOS PAN (single band) image. Another recently developed watershed technique is size-constrained region merging (SCRM), proposed by Castilla et al., (2008). They used a gradient inverse-weighted edge-preserving and smoothing (GIWEPS) method for the gradient image generation, followed by a MC watershed algorithm for over-segmentation. The over-segmented objects (segments) of the image were merged using three parameters: 1) the desired mean size of the output segments (in hectares); 2) the minimum size required for the segments (in hectares); and 3) the desired spatial accuracy of the segment boundaries (in meters). Further, they claimed that based on the conceptual theory of attractors, the watershed techniques are among the best techniques for characterizing the structure of the objects within a RS image. Moreover, SCRM has been implemented as software. However, SCRM lacks a multi-scale analysis. Nevertheless, SCRM provides a reasonable segmentation outputs for urban VHR image segmentation (Marpu et al., 2010). A multi-scale watershed segmentation algorithm has shown increasing interests among the researchers (Wang, 1997, Hay and Marceau, 2004, Castilla et al., 2008). The reasons are: 1) a simple representation of the segmentation problem; 2) the low parameter complexity; 3) a multi-scale representation; and 4) an effective utilization of spectral, spatial, shape, and texture features with the flexibility to include more features via the region merging process, which is devised to minimize over-segmentation (Wang 1997, Hay and Marceau 2004, Castilla et al., 2008 and Zhaocong et al., 2009). Moreover, two watershed techniques, namely SCRM and the basic watershed segmentation algorithm based on MC technique, (in ERDAS Imagine software) have been implemented in software. All of these factors suggest that a multi-scale watershed segmentation technique is a desirable and among popular techniques for urban VHR image segmentation.

3.3.3 HSMR model

Contrary to watershed based conceptual model, HSMR is a top-down approach (split and merge). In RS, one of the early applications of the concept of split and merge was proposed by Cross et al., (1988). Traditional split and merge techniques often resulted in over-segmentation of the image along with the erroneous boundaries of the segments, especially for VHR images (Ojala and Pietikäinen, 1999). Ojala and Pietikäinen (1999) attributed these problems to the use of inappropriate texture features and proposed a hierarchical split and merge based segmentation technique for enhanced texture based segmentation. HSMR model has three basic steps: a) hierarchical splitting, b) agglomerative merging, and c) boundary refinement. Hierarchical splitting divides the image into blocks of size S_{max} and splits each block into four equal sized regions until a splitting criterion for the block is satisfied or the size of the smallest image region of the block is less than S_{min}, as shown in figure 5(*a*). Both the splitting and subsequent agglomerative merging criteria are based on a texture feature known as local binary pattern (LBP) and a spectral contrast based measure (C), which are derived from the local window based operations on the image. After the agglomerative merging, the generated image boundaries may have blocky appearances, as shown in figure 5 (*b*). These boundaries are refined based on their neighbourhood relationships. Figure 5(*c*) shows a segment after the application of all the three steps of the HSMR technique. The approach has four parameters which are S_{max}, S_{min}, a splitting threshold, and a merging threshold. The LBP texture feature, defined by Ojala and Pietikäinen (1999), was applicable only for grey level images. Hence, the texture feature was suitably modified for color/multi-spectral images by Chen and Chen (2002). Further, Hu et al., (2005) modified the method of Chen and Chen (2002) and proposed an adaptive feature descriptor using colour, texture, and intensity based features for the segmentation of a multi-spectral Quickbird image. Wuest and Zhang (2009) found several discrepancies in the method of Hu et al., (2005) namely, fragmentation and discontinuous boundaries of the generated regions/segments. They proposed a fuzzy logic based HSMR technique for the supervised image segmentation of the images containing only five image classes, namely forest, grass, soil, water, and urban. They used a different boundary refinement procedure to reduce the fragmentation and non-contiguity of regions. Each of the classes was separated by specific indexes derived from spectral, spatial, and shape based features. The technique was applied to an urban Quickbird image. Although the technique generated good results, the technique is restricted to the specified five classes. This restriction is a huge disadvantage of the technique. However, the technique can be extended for unsupervised segmentation as proposed by Wuest and Zhang (2008).

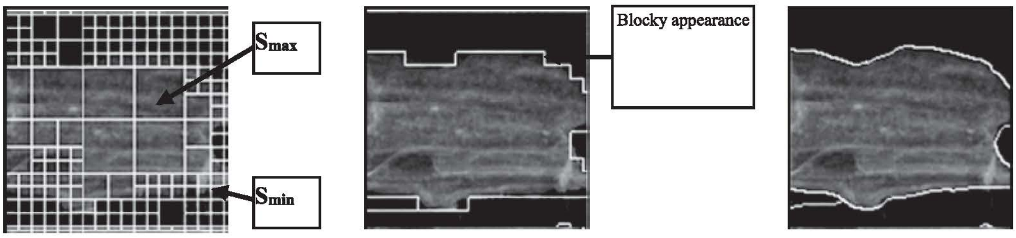

Figure 5: (*a*) shows the hierarchical splitting step with S_{max} and S_{min} as the sizes of the maximum and minimum blocks; (*b*) shows the blocky appearance of the boundaries generated after the agglomerative merging step is performed on the split regions; (*c*) shows the smoothened boundaries after the boundary refinement of the image produced at step (*b*). Source: Wuest and Zhang (2009) Courtesy: ISPRS

HSMR requires a lot of user-defined parameters which is among HSMR's major drawbacks (Hu et al., 2005). Further, the same set of texture or colour features might not be the appropriate features for the discrimination of segments across images of different resolutions and scenes. Nevertheless, HSMR is a relatively new model requiring more research, especially for segmentation of textured VHR images (e.g., urban forest).

4. Summary and Conclusions

4.1 Summary

This study reviewed several recently developed remote sensing image segmentation techniques related to urban land cover detection using the segmentation of an urban VHR image. To create the background for selecting the techniques, several factors which govern the choice/popularity of a particular image segmentation technique were identified. These factors are: i) the number of the used image interpretation elements, namely spectral, spatial, texture, shape, size, context, shadow, connectivity, and association; ii) the use of a multi-scale concept; iii) the level of parameter complexity; iv) the level of complexity in implementation, and v) the use of segmentation evaluation measures. Further, eight major categories related to techniques of urban land cover segmentation using VHR imagery were identified. These categories are: 1) clustering, 2) level-set, 3) MRF, 4) ANN, 5) fuzzy, 6) multi-scale, 7) watershed, and 8) HSMR. Basic concept of each of the categories is briefly explained citing their advantages and disadvantages. This was followed by a brief discussion of recently developed techniques and their potential for urban land cover segmentation using VHR imagery in the view of the above mentioned factors. It is important to note that the number of user-defined parameters and interpretation elements of the techniques mentioned in this paper are as specified by the reviewed research papers, which proposed the techniques. In real applications of the techniques, the number of parameters and use of interpretation elements may vary slightly. Finally, the potential of each technique towards segmentation based classification and feature extraction for urban land cover segmentation has been specified.

4.2 Conclusions Based on the Factors

The factors for the selection of image segmentation techniques have different weight-age for different applications. For example, in the case of the image interpretation elements based factors, it can be concluded that spatial, shape, and prior knowledge based techniques are more favoured because these elements often aid in efficient segmentation. Similarly, the multi-scale concept is the most recognized as well as used concept for complex urban image segmentation. Further, any technique utilizing multi-scale concept gets an upper hand in the selection procedure. This is because multi-scale analysis: 1) represents the objects of urban VHR image at their intrinsic scales (Woodcock and Strahler, 1987 and Hay et al., 2003) and 2) can be integrated in all the categories of image segmentation techniques. Regarding complexity, the complexity in implementation is more difficult to overcome than the complexity related to user-defined parameters. For example, eCognition™'s multi-resolution segmentation technique is popular despite of the technique's user-defined parameter complexity (Blaschke 2010). However, the popularity is also attributed to eCognition™'s ability to provide customized solution and knowledge based fuzzy hierarchical classification (Flanders et al., 2003 and Platt and Rapoza, 2008). The competing software for eCognition™ are ENVI's feature extraction module (since 2008) and Feature Analyst (since 2001). Further, RISA, SCRM and multi-resolution segmentation are a few recently used techniques which are also implemented as software (Castilla et al., 2008 and Blaschke, 2010). To summarize, parameter complexity factor has less weight in selection of image segmentation techniques and can be undermined if a nice to use software for the segmentation technique is available. The final factor is segmentation accuracy assessment/evaluation measures. In spite of considerable progress in evaluation measures, visual assessment is still widely used and required (Corcoran et al., 2010). An object looks visually pleasant after segmentation if it is compact and has smooth borders, which may be obtained with or without using shape features (Neubert et al., 2008). Apart from visual analysis, quantitative evaluation measures are also widely researched. For example, quantitative evaluation measures have wide varieties based on segment area, shape, and geometry (e.g., over-segmentation and under-segmentation), classification accuracy based, and based on object features (Zhang, 1997 and Clinton et al., 2010). However, most of the quantitative evaluation measures are related to efficient identification of a segment or a group of segments. Further, there is lack of global segmentation quality evaluation measures. A few recent global evaluation measures are: 1) proposed by Clinton et al., (2010), which utilizes several quantitative evaluation measures and

2) proposed by Möller et al., (2007), which identify a balanced under-segmentation and over-segmentation result as the best segmentation. Although a few recent approaches have been proposed, a global evaluation measure is required, which is easy to analyse as well as implement. The need of global evaluation measures is further guided by the fact that the visual assessment is subjective and may involve erroneous results.

4.3 Widely-Used Techniques and their Applications

Regarding widely-used techniques, it was found that MRF, ANN, and fuzzy are not popular for urban VHR applications. Most of the earlier clustering, MRF, and FCM based techniques suffer from the identification of an initial number of segments. Hence, the techniques are not attractive for unsupervised segmentation. Moreover, ANN also suffers from modelling complexity, especially for a new user. However, MRF, fuzzy, and ANN techniques may prove useful for supervised segmentation approach or feature extraction and change detection applications, especially fuzzy and ANN techniques because of their customizable properties. This also concludes that the mathematical/probabilistic models are still unable to represent the complex RS ground image. However, a few techniques, of the category of mathematical models, require future research for different urban VHR image segmentation. These techniques are: 1) RISA based on clustering (Wang *et al.* 2010) and 2) FIRME based on fuzzy logic and used for segmentation based classification (Lizarzo and Barros 2010). Contrary to mathematical models, conceptually derived heuristics models (FNEA and watershed) are more popular for VHR imagery. In urban VHR applications, multi-scale analysis is very effective (Blaschke 2010). Multi-scale analysis can be integrated in the techniques of all categories. Multi-resolution segmentation, as implemented in eCognition™ software, is the most widely used segmentation technique in urban VHR image segmentation (Blaschke, 2010). Apart from multi-scale based techniques, watershed segmentation techniques are gaining wide popularity.

Table 2(a): It enlists the major features namely approach, interpretation elements, image, evaluation and application, of techniques described in each of the seven categories of techniques, namely, clustering, MRF, ANN, and Fuzzy, discussed in this review paper

Clustering approach					
Authors method	**Categorisation**		**Image used**	**Evaluation**	**Application**
	Interpretation elements	**Approach**		**Method**	
Wang *et al.* 2010b (RISA)	Spectral, Spatial, Scale,Shape and Size	Region Growing & Merging	SPOT-5 & Quickbird	Classification accuracy	Urban Area (implemented as software)
Li *et al.* (2010)	Spectral, texture, and Shape	Hybrid: Fuzzy Clustering and watershed	Quickbird pansharpened, Aerial and SPOT5	Defined measures for determining over and under segmentation	Agricultural & Urban mixed
MRF model					
Liu et al (2009)	Spectral and spatial context	Region splitting then Merging	Quickbird MS	Based on Mis-segmentation results	Semi-urban
ANN model					
Li et al (2007) (PCNN)	Spectral & Spatial	Point based region growing	IKONOS	Visual Comparison	Urban
Fuzzy model					
Fan et al (2009) (SWFCM)	Spectral, spatial & Prior Knowledge	Cluster growing	Landsat TM	Classification accuracy and cluster validity indices	Agriculture mixed water land
Hasanzadeh and Kasaei (2010)	Spectral and Spatial	Cluster growing	Landsat. -7	Quantitative segmentation accuracy	Agricultural
Lizarzo and Barros (2010) (FIRME model)	Spectral , spatial and contextual	Region growing	Quickbird	Classification accuracy	Urban

Table 2(b): It enlists the major features, namely approach, interpretation elements, image, evaluation and application, of techniques described in each of the seven categories of techniques, namely Multi-scale, watershed, HSMR, and Level set, discussed in this review paper

Multi-scale model					
Baatz and Schäpe (2000)	Spectral, spatial, size and shape	MR segmentation	Almost all VHR RS imagery	Visual assessment	Implemented as Software
Tilton (2003) (RHSEG)	Spectral, Spatial & size	Region growing	Most of RS imagery (not good for VHR image)	Visual assessment	Implemented as Software
MOSA by Hay and Marceau (2004)	Spectral, size, scale and spatial	Region based	IKONOS PAN	Visual assessment	Forest
Blob feature detection (SS) By Hay *et al.* (2003)	Spectral, size, scale, connectivity and spatial	Region based	IKONOS PAN	Visual assessment	Forest
Watershed model					
Chen *et al.* (2006) (Rain- falling)	Spectral, spatial shape, scale and size	Region growing	IKONOS pan	Visual comparison	Urban
Li and Xiao (2007). (Immersion simulation)	Spectral, spatial and size	Region growing	SPOT 5 & Quickbird (QB) MS	Segmentation based classification accuracy	Agricultural mixed urban
SCRM by Castilla *et al.* (2008)	Spectral, shape, size and spatial	Region growing	Quickbird	Visual assessment	Agricultural and urban(Implemented as software)
HSMR model					
Hu et al (2005)	Spectral, texture, size and scale	Region splitting and Merging	Quickbird and IKONOS (MS and PAN)	Visual assessment	Urban
Wuest and Zhang (2008)	Spectral, texture, size and scale	Region splitting and Merging	Quickbird MS	Visual assessment	Urban
Level set					
Karantzalos and Agialas (2009)	Spectral, shape size and scale	Region based	Quickbird	Visual assessment	Urban

The popularity is attributed to its flexibility in handling multiple image features and subsequent region merging after initial over-segmented results. MOSA and SCRM are two promising techniques, which require future research and experimentation on VHR imagery for segmentation (Hay et al., 2003 and Castilla et al., 2008). Level-set and HSMR are recently introduced techniques in the field of urban VHR RS image segmentation. Between the two, level-set has been applied to feature extraction application because level-set techniques utilize vector based operations. However, level-set is still in its infancy, as compared to the techniques of other categories, especially for urban VHR image segmentation. Hence, level-set techniques require further experimentation on VHR images. On the other hand, HSMR suffers from parameter complexity as well as requires efficient discriminative features for fruitful segmentation. However, HSMR may be useful for some heterogeneous land use based segmentation. Based on the techniques reviewed in this paper, the authors believe that HSMR techniques are suitable for only small set of applications, such as a specific feature extraction. Overall, the future prospects of urban VHR image segmentation lies with multi-scale model based and watershed based segmentation techniques for general segmentation applications (e.g., classification, change detection, feature extraction, etc.). Also, image segmentation is in dire need of a global and effective accuracy assessment measure similar to image classification. In addition, RS image segmentation warrants an effective algorithm implemented in an open source software because commercial software are expensive. Table 2(a) and 2(b) summarize the features of the techniques reviewed in this paper under each category namely, clustering, MRF, ANN, Fuzzy, Multi-scale, Watershed, HSMR, and level-set.

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